LearnSync - A Privacy Protected and Federated Adaptive EdTech Learning Platform

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***Abstract* - The goal of providing individualised learning experiences in the field of educational technology is still to protect user privacy. This study proposes a novel solution to this problem by creating a course recommendation system based on Federated Learning. platform, which makes use of Federated Learning, examines user interactions locally on individual devices while protecting data privacy. It then compiles insights globally to produce customised course recommendations. This approach offers consumers personalised learning paths while protecting the privacy of their sensitive data by fusing the strength of machine learning with resilient privacy-preserving strategies. These results highlight how crucial it is for educational technology to strike a balance between privacy and personalisation. By adopting Federated Learning, we open the door to a more inclusive and equitable learning environment while also giving users the confidence to achieve their educational objectives.**

***Keywords* - Federated Learning , Homomorphic Encryption, Local & Global Servers, Personalization , Privacy Protection.**

I. INTRODUCTION

With the fast changing field of educational technology, it is more important than ever to provide students with individualised learning experiences. Conventional one-size-fits-all methods frequently fail to satisfy the varied learning needs of pupils, which results in low learning outcomes and disengagement. Furthermore, issues with data security and privacy present serious difficulties, especially in this day of widespread data collection and analytics. This study presents a revolutionary Federated Learning based course recommendation system that aims to transform how people interact with educational content by addressing the competing demands of privacy and personalization.

A distributed machine learning paradigm called federated learning allows for direct model training on user devices while maintaining the privacy of sensitive data, which presents a strong answer to the privacy conundrum. This technology creates individualized learning routes for users based on their interests, skill levels, and preferred methods of learning by utilising insights obtained from in-person encounters. By using this decentralised method, reducing privacy issues and gaining access to tailored learning opportunities.

Federated Learning also promotes inclusivity and diversity in the recommendation process by utilising the collective intelligence of multiple user groups, guaranteeing that instructional content takes into account the varied requirements and backgrounds of learners. In this paper, we explain this Federated Learning-based course recommendation system's potential to transform education and empower learners globally by delving into its conceptual framework, design considerations, and implementations.

II. RELATED WORKS

Federated Learning has garnered substantial interest from scholars and industry professionals alike, prompting an abundance of research papers that attempt to tackle diverse issues and investigate innovative uses. A homomorphic encryption-based method for Federated Learning was presented by Kurniawan and Mambo (2022), guaranteeing privacy preservation for deep learning applications. Their research paved the way for the integration of cutting-edge cryptographic methods into Federated Learning frameworks, improving distributed learning environments' data security [1] [3]. Xia et al. conducted a survey in which they examined Federated Learning for edge computing, highlighting important research issues and suggesting potential solutions [2]. This thorough analysis clarified the relationship between edge computing and federated learning, opening the door to the creation of scalable and effective learning algorithms designed for edge devices with limited resources.

Furthermore, Brecko et al. offered an extensive overview of current methods and developing trends, offering insights into the use of Federated Learning in edge computing contexts [9]. Their research demonstrated how crucial federated learning is to the development of intelligent Internet of Things applications at the cloud-edge interface and the evolution of decentralised learning paradigms. This research intends to develop Federated Learning approaches and build upon current knowledge by synthesising insights from these important studies, especially in the context of privacy preservation and personalised education. By using creative thinking and thorough experimentation, we want to solve important problems and open the door to more reliable and scalable Federated Learning solutions.

III. EXISTING DRAWBACKS

Even with the advances in educational technology, there are still a number of issues with the platforms that limit their usefulness and user experience. The absence of personalisation in the recommendations and learning materials is one of the main drawbacks. Conventional learning systems frequently take a one-size-fits-all strategy, providing uniform content to every user irrespective of their unique learning preferences and needs. Users may find it difficult to locate pertinent and interesting instructional content as a result of this lack of personalisation, which may lower learning outcomes and cause disengagement [4].

Moreover, data security and privacy are issues for the educational platforms that are now in use. As data collecting and analytics have grown in popularity, worries about user data misuse and confidentiality have also grown. Users frequently worry about possible security lapses or unwanted access to their

personal data, which makes them reluctant to provide important information on these platforms. Consequently, establishing strong data privacy protocols and cultivating user confidence become crucial obstacles for providers of educational technology [10].

The incomplete integration of cutting-edge technology like Federated Learning into existing educational platforms is another drawback. Federated Learning is still relatively new in educational settings, but it provides a promising answer to privacy concerns by allowing for decentralised model training. Many current platforms are unable to take advantage of Federated Learning's potential benefits in improving personalisation and data privacy because they lack the infrastructure and knowledge necessary to apply it successfully [9]. Furthermore, it is frequently difficult for the educational platforms of today to instantly adjust to the changing needs of its users. It is difficult to take into account different learning styles and preferences due to the static structure of material distribution and assessment methods[4][11]. Rigid course frameworks and evaluation formats may place restrictions on users, making it more difficult for them to interact and explore learning resources in a personalized and flexible way.

Therefore , there is a need for creative solutions that prioritise user-centric design, strong privacy measures, and seamless integration of cutting-edge technologies like Federated Learning. These solutions are necessary due to the shortcomings of current educational platforms, which include a lack of personalisation, data privacy concerns, limited integration of advanced technologies, and inflexibility in meeting diverse learning needs. To fully realise the potential of educational technology in empowering students and promoting opportunities for lifelong learning, these issues must be resolved.

IV. Proposed Methodology

Federated Learning (FedML) is a novel approach to machine learning that is revolutionising the field by facilitating cooperative model training amongst dispersed edge devices while carefully preserving data privacy. Fundamentally, FedML is based on the privacy-by-design principle, which guarantees that users can actively engage in model training without giving up control over their private, sensitive data. In the context of our initiative, federated learning plays a critical role in transforming the personalised education scene by providing students with unmatched access to personalised learning experiences while upholding the confidentiality of their personal information. FederatedML is based on a cooperative architecture in which edge devices work together to train models without requiring raw data to be sent to a central server. Federated Learning helps to reduce worries about data security and privacy by utilising edge devices' processing power while keeping private data contained on individual devices.

Federated Learning is the cornerstone of this concept, providing democratized access to customised learning opportunities. Learners can take advantage of tailored recommendations and flexible learning paths while maintaining complete control over their personal information by utilising distributed computing. This revolutionary strategy builds a culture of trust and transparency between users and service providers in addition to improving the effectiveness of educational platforms.

Federated Learning, which prioritises data security and privacy while enabling collaborative model training, is, in short, a huge advancement in machine learning. Federated Learning has the potential to completely transform the personalised education space by providing students with unmatched customisation while maintaining the strictest privacy protection guidelines. As we persistently investigate the immense possibilities of Federated Learning, we are resolute in constructing a future in which individualised education is inextricably linked to autonomy and privacy.

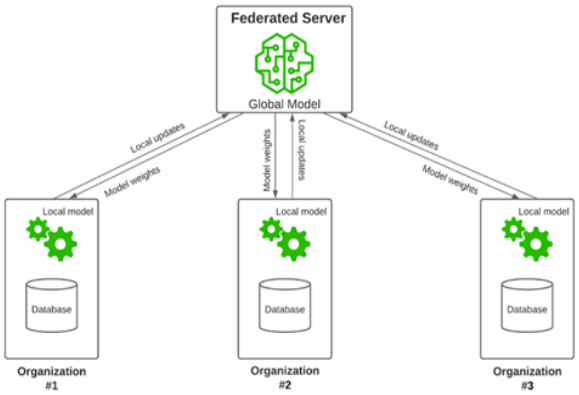

Figure 1. Generic architecture to show Federated Learning working with the help of local and global models.

This project consists of a number of essential components, each of which is essential to the platform's smooth operation. The main point of engagement is the React.js-based user interface, which gives users easy access to learning materials and tailored recommendations. By using local model training on edge devices on the backend, the solution permits users to contribute their data without sacrificing privacy. After being trained locally, these models are combined to create a global model, which protects user privacy and allows for improved learning insights. Furthermore, an encryption module guarantees end-to-end security, safeguarding private user data while it is being learned. In order to facilitate effective data storage and retrieval, the platform also incorporates features like recommendation systems, statistical analysis pages, test modules, and an extensive home page. All of these elements work in unison with MongoDB. This project aims to transform education by bringing these modules together and creating individualised learning experiences that put the privacy and empowerment of the user first.

A. User Interface

This project's user interface module acts as a smooth and user-friendly entry point for users to engage with the educational platform. The website, which was created with React.js, has an engaging landing page that effectively summarizes This project's goals, team members, and importance in the field of personalised education. The landing page also invites viewers to explore deeper by providing a thorough rundown of all the features and functionalities of the site. When users visit the platform, they are greeted with a screen that allows them to sign up or log in, depending on which option they choose to use to access the services available on the platform. Upon logging in, users are met with a dynamic homepage that functions as the focal point of their learning experience. The homepage features a handpicked assortment of

courses that users have chosen, courses that are suggested based on their learning style and past experiences, and well-liked courses that are currently trending among platform users. Users are guaranteed to be shown interesting and pertinent content that is catered to their unique interests and learning goals thanks to this personalized approach.

Additionally, the platform has a dedicated statistics page where users may obtain insightful information about their performance and learning progress. Users can visualise their performance in class, manage their learning objectives, and track their academic progress over time with interactive charts and graphs. Users are empowered to make well-informed decisions regarding their learning tactics and areas for growth thanks to this data-driven approach.

The portal features a test page where users can take scheduled examinations to evaluate their knowledge and skill in various disciplines, in addition to performance tracking and personalised recommendations. Users receive personalised recommendations based on their exam results, pointing them in the direction of areas to focus and additional learning opportunities.

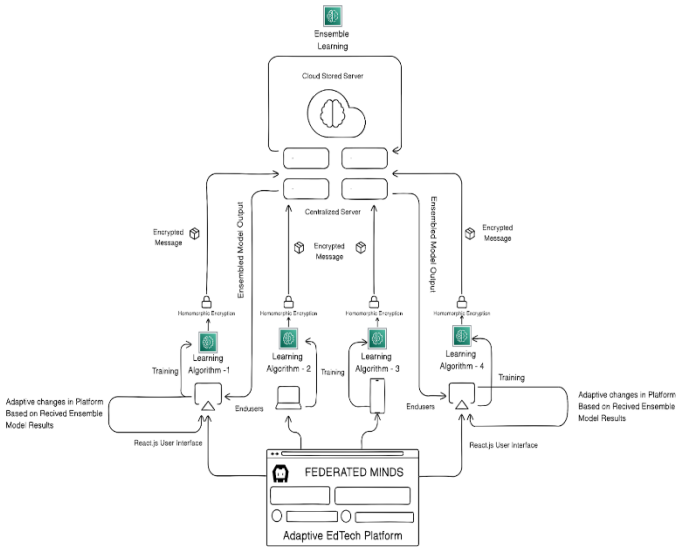

Figure 2. System Architecture of the project showcasing all the modules and the data transfer among them.

Last but not least, the platform has a user profile page that acts as a primary location to manage user data and activities. Viewing their courses enrollments, monitoring their progress, and receiving tailored recommendations based on their past learning experiences are all available to users. By encouraging a sense of accountability and ownership, the profile page gives users the tools they need to effectively take charge of their educational journey and meet their learning objectives. All things considered, the user interface module is essential to provide a smooth, interesting, and customised learning experience, which propels the popularity and success of our learning platform.

B. Centralized Database

This project uses MongoDB as our centralized database storage solution in this project because it offers a reliable and scalable architecture for managing and storing important data assets. A number of collections are created within the MongoDB cluster to arrange and store different datasets and data that are necessary for the platform's operation.

A carefully selected collection of learning data for every user is contained in the Dataset_users collection, which acts as a repository for pre-made datasets. The thirty rows of data in each dataset include vital parameters including the course ID, the amount of time spent on learning activities, quiz scores, quiz attempts, and performance indicators. A new row is automatically attached to the corresponding user's dataset after every prediction generated by the platform, allowing for tracking and analysis of continuous learning. Comprehensive information about every course that is offered on the platform is stored in the courses collection. Users who have enrolled, their performance metrics, and other pertinent information are saved for each course. Our collection serves as a central location for tracking user progress, organizing courses enrollments, and compiling performance information from various modules and disciplines.

Additionally, the user's collection keeps an exhaustive log of all users who have registered, keeping track of relevant user data as well as their chosen courses and associated information. The foundation of user management, authentication, and access control is provided by this collection, guaranteeing smooth user interfaces and tailored interactions across the platform. Furthermore, the questions collection has a wide range of exam questions for every subject that is available on the platform. Users can efficiently evaluate their knowledge and skill in particular disciplines by using these questions to build and schedule tests.

Additionally, playlist IDs are stored in the playlists collection and are used in the YouTube API to search for and get pertinent instructional content. The platform enhances the educational experience by utilising playlists to offer carefully selected sets of additional resources and instructional materials that are in line with the interests and learning goals of the user. All things considered, MongoDB forms the cornerstone of this project's architecture, enabling effective data management, retrieval, and storing across several collections. MongoDB facilitates smooth integration and communication between various modules by structuring data in a scalable and organised manner, assuring the best possible performance and dependability for this learning environment.

C. Local Model

An essential part of this federated learning architecture is the local model, which is the main machine learning model that is trained on each edge device with locally accessible datasets kept in the MongoDB infrastructure. Its goal, based on supervised learning data unique to each user's learning activities, is to forecast user performance using a basic regression model.

The local model employs a regression-based methodology and integrates four critical elements to precisely forecast user performance. These variables include the quiz attempts, test results, amount of time spent on learning activities, and courses ID. Custom weights are assigned to each factor, influencing their relative contributions to the overall forecast, in order to

provide optimal predictive performance. The weights, which are represented by the numbers [0.001, 0.4, 0.8, -0.02], have been carefully selected to represent the relative significance of each input variable in influencing user performance. From a mathematical perspective, the regression equation that controls the predictive functionality of the local model is as follows,

$$\text{Performance}=0.001\times\text{time_spent} + 0.4\times\text{test_scores} + 0.8\times\text{quiz_attempts} + (-0.02\times\text{course_ID})$$

Once user performance data for the chosen subject has been gathered, predictions about user performance levels are produced using the local model. The estimated performance results, classified as fair, good, or bad, are then saved back into the courses collection of the MongoDB database along with the user's unique ID and the courses they choose. The platform retains real-time insights into user performance across many learning modules, enabling adaptive and personalised learning experiences, thanks to the smooth integration of local model predictions into the database.

D. Homomorphic Encryption

One innovative cryptographic method that makes encrypted data usable for computations without requiring decryption is homomorphic encryption. In plainer language, it makes it possible to execute operations like addition and multiplication directly on encrypted data, yielding results that, upon decryption, are identical to those produced by carrying out the same operations on unencrypted data. This special characteristic of homomorphic encryption guarantees the complete encryption of sensitive data during the computing process, protecting security and privacy.

In this project, the federated learning framework's homomorphic encryption module is essential to improving user data security and privacy. To be more precise, these predictions are written back to the database after being encrypted using homomorphic encryption techniques, which are obtained from the MongoDB database. We guarantee that confidential user performance data stays out of the hands of unauthorised parties, including the global model, by encrypting the forecasts. After encryption, the forecasts are safely kept in the MongoDB database until the global model has a chance to process them further. The global model can easily access and use this encrypted data without jeopardising the privacy of specific users. The federated learning system gains a strong privacy layer that protects user data and facilitates cooperative model training amongst decentralised edge devices, thanks to the integration of homomorphic encryption.

E. Global Model

Across all participating edge devices in the federated learning system, the global model acts as a central entity that aggregates local model predictions. The global model produces thorough insights and recommendations by utilising the collective knowledge contained in these encrypted forecasts. The global model starts the aggregation process to create a single forecast that represents the overall performance trends of the user base after it receives all encrypted local model predictions for a specific topic from the MongoDB database. The weights allocated to each local model prediction are determined depending on the performance of the related student, and this is where the aggregation process starts. This formula is used to calculate these weights:

$$\text{weights}_j = \text{student_marks}_j \,/\, \sum_{i=1}^{n} (\text{student_marks}_i)$$

$$aggregated_performance = \sum_{i=1}^{n} local_prediction_i \times weights_i$$

Each student's performance results are represented by student_marks and n is the total number of students who have opted that course. These weights ensure that users with higher performance have a bigger influence on the outcome by indicating the relative value of each student's input to the aggregated prediction. The global model then uses the weighted local forecasts to get the aggregated prediction, which provides a consolidated view of the subject's overall performance. The final result is obtained by the global model decrypting the aggregated prediction when the aggregation procedure is finished. This decryption prediction incorporates insightful information gleaned from the user base's combined knowledge, offering a thorough assessment of performance trends in the intended topic. After decryption, the global model makes sure that this new prediction is integrated into the MongoDB database so that it may be easily accessed for additional analysis and suggestions.

The global model enhances the user's dataset by adding a new row combining performance measurements and the globally predicted performance measure, in addition to updating the MongoDB database with the decrypted forecast. By adding the most recent insights from the federated learning process to the user's dataset, this augmentation gives users access to recommendations and personalised comments that are specifically catered to their own learning paths. The central component of This federated learning system is the global model, which plays a crucial role in combining and combining encrypted local model predictions. The global model maintains the highest levels of data security and user privacy while also promoting holistic learning experiences through the harmonization of decentralized findings into coherent suggestions. By utilizing the combined intelligence of dispersed edge devices, the global model promotes collaborative learning models that can adjust to the various requirements and inclinations of individual users.

F. Recommendations and Personalization

After the global prediction is generated, this system leverages this information to customise personalised recommendations for every user, resulting in an interactive learning process that corresponds to their specific skill levels. This recommendation system determines the best courses of action for users based on the globally expected performance measure and subject dictionaries. This includes examining basic concepts, going deeper into more complex subjects, or refining abilities through focused practice sessions. By using an adaptive approach, users' educational journeys are optimized and recommendations are made based on their present aptitude and learning trajectory. The first step in the suggestion process is to compare the globally expected performance measure to an extensive subject’s dictionary that contains a variety of courses arranged based on learning objectives and difficulty levels.

This algorithm creates a customised list of suggested courses based on this data, taking into account each user's learning interests and skill level. These suggestions cover a wide range of topics at the beginning, middle, and advanced levels, giving users lots of chances to learn new ideas and hone their current abilities.

This system creates customized recommendations and then updates the MongoDB database with the user's customized courses list, allowing for easy access to individualised learning paths. The recommendations are presented as interactive cards that visitors can explore at their convenience and are prominently displayed on the home page under the "Recommendations" section. A clickable link on each recommendation card points visitors to carefully chosen playlists that go along with the suggested courses, allowing for a smooth transition between finding courses and consuming content.

Through the provision of tailored suggestions based on the subject and global prediction dictionaries, this system enables users to start a learning path that corresponds with their specific objectives and desires. Whether users want to focus on honing a particular ability, learn a new subject, or grasp fundamental ideas, this recommendation engine acts as a lighthouse, pointing users towards individualised learning paths. This solution enables a comprehensive learning experience that surpasses conventional limitations by integrating recommendation cards and carefully selected playlists in a seamless manner. This empowers users to reach their maximum potential while pursuing knowledge and personal development.

G. Sequence, Data and Module Workflow

With an interface driven by React.js, this federated learning-based educational platform ensures accessibility and engagement while providing a user-centric experience. Visitors choose among courses that are catered to their interests on the login and register pages after navigating a friendly landing page that includes detailed project information. With the help of a comprehensive MongoDB question bank, users may assess their level of skill and receive tailored recommendations on a dedicated exam page that caters to a variety of learning requirements. A centralised user profile makes it simple to track personalised learning experiences, allowing for well-informed decisions regarding course engagement and advancement.

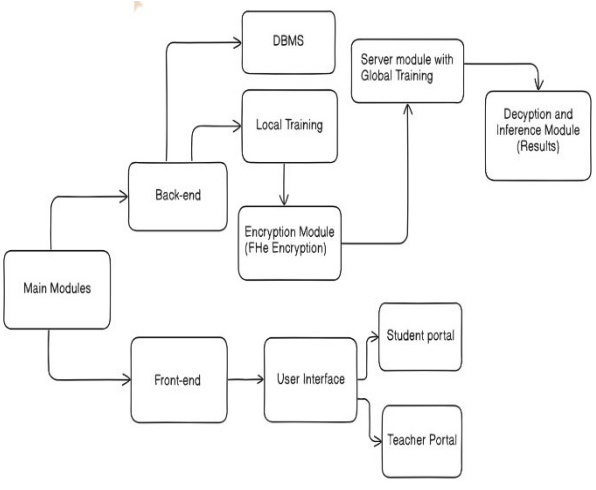

Figure 3. Module Decomposition Diagram to depict all the main modules involved in the project.

The local model, which is the foundation of the platform, uses supervised datasets and adjustable weights in conjunction with regression analysis to forecast user performance indicators. To ensure seamless worldwide aggregation, these forecasts are encrypted for privacy using homomorphic encryption techniques. After that, the global model combines encrypted local forecasts to produce thorough performance trends. This protects user privacy and provides personalised suggestions depending on competency levels. The main page's interactive recommendation cards lead viewers to carefully chosen playlists for enhanced educational opportunities while blending in smoothly with user interfaces. This platform essentially combines recommendation engines, encryption methods, model training, user interface design, and database storage to support customised learning experiences that encourage ongoing development and empowerment in the quest for knowledge.

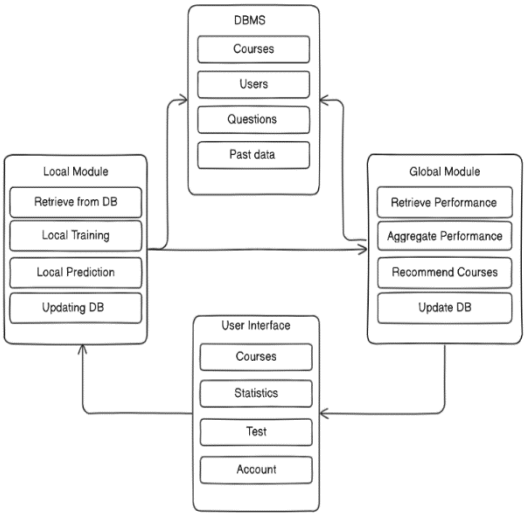

Figure 4. Component Design Diagram showing component interaction to produce the recommendations for the user.

V. LIMITATIONS AND FUTURE ENHANCEMENTS

This federated learning-based educational platform has some limits and need for improvement, even if it offers promising opportunities for personalised learning and data privacy protection. One significant issue is that local models are trained using pre-made datasets, which can cause model drift and lower predicted accuracy over time. In order to address this, upcoming versions might include mechanisms for continuously retraining the model and creating dynamic datasets to guarantee adaptation to changing user behaviour and learning styles. Furthermore, when the user base grows, the computational burden brought about by the homomorphic encryption module might affect scalability and performance. Future developments could investigate hardware accelerators and encryption technology optimisations to preserve strong privacy guarantees while boosting computational efficiency in order to lessen this.

Additionally, even while the present recommendation engine aims to provide personalised recommendations, accuracy and diversity should yet be enhanced. In order to provide more contextually appropriate recommendations, future iterations may make use of sophisticated machine learning techniques like collaborative filtering and natural language processing. Furthermore, encouraging group learning and information exchange among users may improve the platform's usefulness.

Including social learning components in the form of discussion boards and group projects can improve student learning and encourage community involvement. Overall, maintaining the platform's long-term relevance and efficacy will require embracing a culture of constant innovation and adapting to changing user expectations and educational trends.

VI. Conclusion

This federated learning-based learning platform is a ground-breaking method of individualised instruction that both protects user privacy and data security. Through the utilisation of homomorphic encryption and decentralised edge devices, we have created a solution that is both scalable and privacy-preserving, enabling learners to access customised learning experiences without jeopardising sensitive data. This platform produces comprehensive insights and recommendations by means of collaborative model training and local prediction aggregation. This enhances the learning experience for people and promotes a sense of community and teamwork.

Even though This platform shows great promise for revolutionising education, it is critical to recognise its inherent shortcomings and possible areas for further development. The efficiency, efficacy, and scalability of federated learning systems can only be improved with continued study and development due to obstacles including model drift, computing overhead, and scalability limits. Furthermore, achieving regulatory compliance, guaranteeing strong security protocols, and promoting inclusivity and accessibility are critical to maximising the potential of This platform in various educational settings.In the future, federated learning will be essential to democratising access to high-quality education, empowering students from diverse origins and skill levels to prosper in an increasingly digital and connected society. We can keep pushing the limits of educational technology, generating good societal impact and enabling people to reach their full potential through individualised and inclusive learning experiences, by embracing innovation, teamwork, and a dedication to user-centric design.

VII. Declaration

1. Competing Interests: Not Applicable.
2. Funding Information: Not Applicable.
3. Author Contributions: All authors contributed equally to this work. Shreyas R S, Kollipara Sai Sandeep , Somula Jaswanth Reddy and Vivek Pandith D V were involved in the conception, design, data collection, and analysis of the study. Dr. Jyothi D G, as the academic guide, provided critical revisions and important intellectual content throughout the research and manuscript preparation process.
4. Data Availability Statement: Not Applicable.
5. Research Involving Human and/or Animals: Not Applicable.
6. Informed Consent: Not Applicable.

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